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Chapter 5

Short- and Long-Run Dynamics of Speculative-Grade Bond Yields

5.1 Introduction

Like Treasury securities, corporate bonds provide a return to investors for saving and forgoing consumption today. Until the early 1980s only the highest-quality firms could issue marketable debt. During the 1980s a market emerged for speculative-grade debt. This allowed more default prone firms to issue bonds as well, which are known as high-yield or junk bonds.

When underlying credit quality decreases rational investors will require an increasingly higher yield to be compensated for potential losses due to default. However, empirical studies, like Fons (1987) and Hull, Predescu and White (2005), document that risk neutral default probabilities in general exceed actual default probabilities. Alternatively stated, on average investors in corporate debt seem to require a spread over the risk-free rate in excess of expected default losses, see also Altman and Bencivenga (1995) and Amato and Remolona (2003).

For one thing, subjective default probabilities may simply be higher than those obtained from historical data. Discrepancies might also be ascribed to differential tax treatment of corporate and government bonds, and systematic risk premiums, see Agrawal, Elton, Gruber, and Mann (2001). Moreover, corporate bonds trade in relatively thin markets as compared to Treasury bonds. Liquidity therefore seems to be an important determinant of corporate bond yields, especially in the high-yield segment, see Cornell (1992). Finally, the typically skewed bond return distribution makes it much more difficult to diversify risk, see Amato and Remolona (2003). As a result idiosyncratic risk may be priced as well. Driessen (2005) reveals that liquidity, tax, and systematic risk premia are important determinants of excess returns on investment-grade bonds. A risk premium associated with a price jump in case of default explains a significant part of excess returns as well, though it cannot be estimated with high statistical precision.

Even when investors require a spread over the risk-free rate in excess of expected default losses, we might still expect that a unit change in expected default loss would be fully reflected in corporate bond yields in the long-run.

This chapter gives additional insight into short- and long-run dynamics of speculative-grade bond yields for the period 1991-2007. We use subindices of the Merrill Lynch U.S. Corporate Master Index, the U.S. High Yield Master II Index and the U.S. Treasury Index, see Merrill Lynch (2000).

When variables are integrated of order one but cointegrated, differencing would be counterproductive. Indeed, a cointegrated system can never be represented by a finite-order autoregressive relation, see Hamilton (1994). As a result we first estimate a fundamental long-term relationship between corporate bond yields on the one hand, and Treasury yields and historically estimated default losses on the other. Subsequently an error-correction model is formulated that describes the variation in yields around long-run values in terms of a set of stationary variables, including the equilibrium error of the cointegration relation. In this way we preserve the information of both short- and long-run relations between variables.

Our approach is related to Barnhill, Joutz, and Maxwell (2000) who study the CS First Boston Composite High Yield Index, as well as the BB and B segments of the high yield bond market for the period 1987-1996. We extend their study in two main directions.

First, apart from Treasury yields and default rates we incorporate bond recovery rates in the cointegration relationship. Lacking data, empirical studies frequently fix bond recovery at around $40 per $100 face value, see Altman and Kishore (1996). Recovery itself can of course vary greatly through time. Our estimated average senior unsecured recovery rate on straight bonds ranges from about $20 to $70 per $100 face value. Moreover, default and recovery rates are negatively related, see also Cantor, Hamilton, Ou, and Varma (2006).

It seems intuitive that default and recovery rates are affected by similar economic factors in an opposite direction. For example, Altman, Brady, Resti, and Sironi (2005) indicate that the negative correlation should predominantly be ascribed to a high (low) supply of distressed assets of defaulting issuers during downturns (upturns), versus a relatively fixed demand of investor being active in this niche market.

In sum, if a long-term relationship between corporate bond yields, Treasury yields and variables related to default risk exists, it is necessary to account for bond recovery dynamics. Incorporating bond recovery is also in line with previously mentioned papers, which relate yield premiums to historically estimated default losses in a static way.

Second, bond indices represent a blend of maturities. Keeping the underlying rating category fixed, the Merrill Lynch bond indices allow us to differentiate among different maturity ranges. Merton (1974) already shows that credit yield spreads as a function of maturity of low, medium and highly leveraged firms are upward sloping, hump-shaped and downward sloping, respectively, see also Jarrow, Lando, and Turnbull (1995). Similarly, the impact of parameter changes within the contingent claims setting may not be uniform across different maturity ranges. For example, when leverage ratios are high the marginal impact of volatility changes decreases in bond maturity. Alternatively, Johnston (1968) already suggests that it takes time before negative shocks lead to financial difficulties. Yield spreads on short-term bonds might therefore react less severely to deteriorating economic circumstances than long-term bonds. On the other hand, short maturity bonds most likely need to be refinanced in the bond market in the near future. Given deteriorating economic circumstances this may become significantly more difficult (i.e., crisis at maturity), especially as far as speculative-grade issuers are concerned. Overall, it seems most appropriate to differentiate among different maturity ranges.

We find cointegration relations between speculative-grade bond yields, Treasury yields and estimated default loss. The estimated default loss coefficient should be equal to one when default loss changes are fully incorporated in yields in the long-run. This coefficient is indeed close to its theoretical value when it is possible to use rating specific default rates to estimate default losses. When this is not possible, default losses are estimated by means of speculative-grade default rates. If rating specific default rates are lower (higher) than speculative-grade default rates the corresponding coefficients on the default loss variables will be understated (overstated).

Cointegration relations also reveal that average expected excess returns of corporate bonds over Treasuries increase when ratings decrease. This is in line with Altman and Bencivenga (1995), Amato and Remolona (2003) and Hull et al. (2005).

Like long-run dynamics, short-run dynamics of investment-grade yields are predominantly driven by Treasury yields. Besides bond liquidity and changes in default loss, short-run dynamics of speculative-grade yields are determined by changes in short rates and stock market volatility. The latter is in line with structural models, see Merton (1974). Unlike Barnhill et al. (2000), we do find a clear January effect with respect to speculative-grade bond yields. This can most likely be ascribed to window dressing, see also Cooper and Schulman (1994).

Splitting bond indices up across different maturity ranges, and holding maturity fixed, reveals similar long-run dynamics within rating categories. However, it seems that short maturity bonds respond more vigorously to changes in default losses.

Short-run adjustment to long-run errors depends on the maturity range considered. Consistent with Merton (1974), we also obtain dissimilarities across maturity ranges with respect to changes in the short rate and stock market volatility. Apart from these cases, explanatory variables in general have a uniform impact within specific rating categories. Differences show up predominantly across rating categories.

Finally, though explanatory power is comparable, expected loss specifications are to be preferred over specifications that only incorporate default rates, both from a theoretical and empirical point of view. Estimated coefficients on the default loss variable are more significant and robust across alternative model specifications.

The remainder of this chapter is organized as follows. Section 5.2 describes the data. Section 5.3 discusses the empirical results. Section 5.4 concludes.

5.2 Data

To study the long- and short-run dynamics of corporate bond yields we consider (subindices of) the Merrill Lynch high grade U.S. Corporate Master Index, the U.S. High Yield Master II Index and the U.S. Treasury Index for the period 1991-2007, see Merrill Lynch (2000).[1] Our main interest centers on the (cash pay) Merrill Lynch U.S. High Yield Master II Index, and subindices derived from this broad index (i.e., in terms of rating and maturity). Based on composite ratings of Moody's and Standard & Poor's the Master II index tracks the performance of speculative-grade U.S. denominated corporate bonds, publicly issued in the U.S. domestic market. Qualifying bonds must at least have one year remaining to maturity, a fixed coupon schedule, and minimum amount outstanding of $100 million. At the end of each month bonds are added and removed from the index according to the specified criteria.

5.2.1 Explanatory Variables

In general bond holders are exposed to three broad risk categories: Interest rate risk, liquidity risk and credit risk.

To construct variables related to outright default risk it is important to know both the probability of default and the estimated recovery rate once a default occurs. In line with Fridson and Jonsson (1995), Fridson and Garman (1998) and Barnhill et al. (2000)

[1] Unless otherwise noted all variables are obtained from Thomson Financial Datastream.

we use U.S. 12-month trailing issuer-weighted default rates to capture changes in default probability. These are standard Moody's default rate indicators, see for example Cantor, Hamilton, Ou, and Varma (2004).

Similarly, we construct U.S. 12-month trailing bond recovery rates using the May 2007 version of Moody's Default Risk Service (DRS) database. Like the trailing default rates, this allows for a reasonable number of observations to estimate recovery rates on a monthly basis, for defaults are unevenly spread out across time. The DRS database contains bid prices on defaulted bonds observed roughly 30 days after the date of default, measured per $100 face value.

Every month we estimate issuer-weighted mean recovery rates. These are estimates of recovery rates on portfolio's that are well diversified across issuers. This seems to be appropriate given the bond indices considered. That is, we estimate mean recovery rates for each issuer that defaulted, and subsequently average these estimated recovery rates across issuers.[2]

Recovery rates of course depend on the type and characteristics of the underlying security (e.g., seniority). The Merrill Lynch High Yield Master II index predominantly contains senior unsecured bonds. Moreover, the main category of bond defaults contained in Moody's DRS database are senior unsecured regular bonds. As a result we restrict ourselves to the latter category to estimate 12-month trailing bond recovery rates.

To further identify important drivers of yield changes we rely on Merton (1974), who considers equity as a call option on firm value, and debt as a combined portfolio of riskless

[2]This is also in line with the way Moody's reports recovery rates. Considering a yearly, instead of a monthly, update our estimates are very close to Cantor et al. (2006), exhibit 29.

debt and a written put option. When the underlying creditworthiness of a company deteriorates, default risk, represented by the value of the written put option, becomes relatively more important as compared to plain interest rate risk.

In line with the contingent claims setting we include the *3-month Treasury bill rate* as an explanatory variable. An increase in the risk-free rate would increase the yield on high yield bonds, though it decreases bond spreads.[3]

We obviously expect higher yields in a more risky environment. We include the *Volatility Index (VIX)* of the Chicago Board Options Exchange (CBOE), which is a market estimate of expected volatility. It is calculated using Standard & Poor's 500 index option bid/ask quotes. VIX measures market expectations of near term volatility using nearby and second nearby out of the money put and call options with at least eight days left to expiration, and weights them to yield a constant, thirty-day expected volatility measure of the S&P500 Index.[4]

Within the contingent claims setting it is also clear that the correlation between equity and debt value will be higher when the written put option becomes relatively more important (i.e., high leverage firms). At the firm level we expect a negative association between equity returns and yields, especially so when we consider the high yield market segment. For we have no equity index that is solely related to speculative-grade debt

[3]In particular, considering debt with maturity T and nominal value $D_T = D$, we can denote its yield by $y(r) = \frac{1}{T}\log\frac{D}{D_0(r)}$, where all parameters other than the risk-free rate r are suppressed. So, $\frac{\partial y(r)}{\partial r} = \frac{-\frac{\partial}{\partial r}D_0(r)}{TD_0} \in (0,1)$.

[4]From 2003 onwards VIX has been constructed differently, see CBOE (2003). Most importantly, the index is constructed using options on the Standard & Poor's 500 index, rather than the Standard & Poor's 100 index. The calculation methodology has changed as well (e.g., a wider range of strike prices). Though it is closely related to the old version, we use the latest VIX version.

issuers we simply use the *Standard & Poor's (S&P) 500 composite index* to proxy for changes in equity value.

To proxy more directly for current credit market conditions we include three different variables related to rating assignments. Besides bid prices on defaulted bonds the Moody's DRS database also contains issuer ratings. Though different bonds of a specific company might receive a different rating (e.g., different seniority), a company's issuer rating reflects the (implied) long-term senior unsecured rating.

We first determined the *rating drift* within a specific month, defined as the number of positive minus the number of negative rating changes. We scale this number by the number of rated issuers, which more than doubles during our sample period. Second, we incorporate the *fraction of issuers receiving a speculative-grade rating*, which proxies for the overall credit quality of the population of rated issuers. The expected signs on these two variables are negative and positive, respectively. Finally, like Barnhill et al. (2000), we include variables related to *minor rating classifications* (e.g., the fraction of Ba rated issuers rated Ba3). We expect positive coefficients with respect to these variables.

To determine the importance of corporate bond liquidity, we include both *liquid assets held by mutual funds* and *net new cash flows of mutual funds*.[5] Both variables are scaled by mutual funds' aggregate net asset value. Mutual funds are significant players in corporate bond markets. Both variables are obtained out of publications by the Investment Company Institute (ICI). Net new cash flows are defined as new sales minus redemptions

[5]Instead of net new cash flows we could have used net portfolio purchases of mutual funds. Both series are, not surprisingly, highly correlated such that results could be interpreted in this alternative way as well.

plus net exchanges, where the latter is the difference between sales- and redemption exchanges. Exchanges are money transfers amongst mutual funds. Warther (1995) finds a positive relation between mutual fund flows and bond returns. Fridson and Jonsson (1995) find that net new cash flows (liquid assets) of high-yield mutual funds tend to be associated with a lower (higher) yield spread and an increase (decrease) in the price of speculative-grade securities.

Current U.S. economic activity within a specific month is measured by the *Chicago Fed National Activity Index (CFNAI)*[6], which was originally developed by Stock and Watson (1999). CFNAI is a weighted index of 85 economic indicators. Historically the index has been a useful guide to identify whether the economy slipped into and out of recessions, as identified by the National Bureau of Economic Research (NBER).

Besides current economic conditions we include *lagging* and *leading economic indicators* as well. We use the Conference Board Leading Economic Index^{TM} and the Conference Board Lagging Economic Index^{TM}. These indices are composite averages of ten and seven individual leading and lagging economic indicators respectively.[7]

To capture a possible January effect we include *seasonal dummies*. For one thing, relatively low yields in January might be explained by a tax-loss selling strategy, see Chang and Pinegar (1986). On the other hand, it could be the result of year-end selling by portfolio managers to prevent high-yield debt from appearing in financial reports, see Lakonishok, Shleifer, Thaler, and Vishny (1991) and Cooper and Schulman (1994).

[6] Background information on CFNAI can be obtained from http://www.chicagofed.org.

[7] Background information on the published economic indices of the Conference Board can be obtained from http://www.conference-board.org.

Alternatively, it could simply be ascribed to coupon payments, which may lead to an increase in fund flow in December and a decrease in fund flow in January. In line with Barnhill et al. (2000) we include both December and January, as well as June and July dummies to differentiate between these alternative hypotheses. If the coupon-payment theory prevails we would expect to obtain a similar effect with respect to both dummy pairs.

Finally, we specify *event dummies* to capture overall yield changes as a result of exceptional events. Their eventual impact would not only be hard to capture by the other explanatory variables, it might also affect their estimated coefficients. First, we include March and April 1991 dummy variables to deal with the aftermath of the first gulf war. Second, we incorporate October and November 2001 dummies, to capture the initial impact of the September 2001 terrorist attacks. Finally, following the U.S. 2001 recession, which according to the National Bureau of Economic Research (NBER) officially ended in November 2001, investors have witnessed some of the largest bankruptcy filings in U.S. history.[8] What is worse, these defaults were frequently associated with large corporate scandals. Looking at yield changes, and possibly depending on specific market segments considered, lost confidence seems to show up in the period May to July 2002. We therefore include dummy variables for these months as well.

[8]From Moody's DRS database: Enron Corp. (December 2001), Global Crossing Ltd. (January 2002), Worldcom Inc. (July 2002), United Airlines (UAL) Corp. and Conseco Inc. (December 2002).

Table 5.1: Correlations and Principal Components

Notes: This table presents covariances/correlations and principal component weights related to (differenced, standardized) bond yields of rated subindices of the Merrill Lynch U.S. Corporate Master Index and the U.S. High Yield Master II Index. The sample period runs from February 1991 to April 2007. The left hand side of the table presents the correlation matrix. The right hand side of the table presents fractions of total variance explained by the five principal components, as well as the estimated weights of the first two principal components.

Correlation Matrix						% explained by Principal Components	Principal Component Weights	
	AAA-AA	A-BBB	BB	B	CCC-C		First	Second
AAA-AA	1.00	0.96	0.36	0.13	0.07	0.54	-0.42	0.57
A-BBB	0.96	1.00	0.44	0.29	0.20	0.31	-0.48	0.47
BB	0.36	0.44	1.00	0.57	0.53	0.09	-0.49	-0.17
B	0.13	0.29	0.57	1.00	0.70	0.06	-0.44	-0.43
CCC-C	0.07	0.20	0.53	0.70	1.00	0.01	-0.40	-0.49

5.3 Empirical Results

5.3.1 Pooled

We first consider five yield series differentiated by broad rating classes: AAA-AA and A-BBB series, which are subindices of the U.S. Corporate Master Index, and the BB, B and CCC-C series, which are subindices of the U.S. High Yield Master II Index.[9]

Table 5.1 gives the correlation matrix of differenced yield series (i.e., stationarity). It is clear that the correlation between the investment-grade indices is very high, whilst correlations between these indices and speculative-grade indices are much lower. Correlations between speculative-grade indices are lower than correlations between investment-grade indices.

[9] A further subdivision of the investment-grade subindices would only be possible from 1997 onwards. For our interest centers on speculative-grade bonds, and the correlation between the constituent series of the two high grade indices is quite high (i.e., as observed since 1997), we stick with the AAA-AA and A-BBB series.

Estimating principal components[10] with respect to the standardized (differenced) series, with covariance matrix equal to the reported correlation matrix, we observe that the first two principal components account for 85 percent of the variation. The first principal component gives equal weight to all indices. Still explaining more than 30 percent of the remaining variation, the weights of the second principal component on the investment-grade and speculative-grade indices point in the opposite direction. Though this result might be somewhat affected by outliers, the pattern is actually quite consistent over time if we, for example, calculate these statistics repeatedly using five year rolling periods. Similarly, leaving the noisiest CCC-C series out gives comparable results.

Long-Run Dynamics

The promised yield on a corporate bond, Y, required to break even with the yield on a comparable U.S. Treasury security (i.e., apart from default risk), Y^f, is approximately given by: $Y = Y^f + (P \times LGD)$, where P and LGD denote the default probability and the loss given default, respectively.[11]

Given this relation, Fons (1987) and Hull et al. (2005) document that implied risk neutral default probabilities exceed average corporate bond default probabilities. Alternatively, using historical default rates, Altman and Bencivenga (1995), Amato and Remolona (2003) and Hull et al. (2005) show that investors in corporate bonds require a spread over Treasury rates in excess of expected default losses.

In line with this research, we examine a potential long-term relationship between

[10]See, for example, Johnson and Wichern (2002).

[11]See, for example, Altman and Bencivenga (1995) for a more general expression (e.g., incorporating lost interest).

corporate bond yields, Treasury yields and historically estimated default losses. Instead of comparing historical averages of individual series, we take a time series perspective. Even when investors require a spread over the risk-free rate in excess of expected default losses, a unit change in expected default loss might still be fully reflected in corporate bond yields in the long-run.

Barnhill et al. (2000) consider a long-term relationship as well. However, they relate corporate bond yields to Treasury yields and historically estimated default rates only. This means that they refrain from changing recovery rates over time. Our estimates reveal that senior unsecured recovery rates on straight bonds range from $20 to $70 per $100 face value. Moreover, default and recovery rates are negatively related, see also Cantor et al. (2006). If there is a long-term relationship between corporate bond yields, Treasury yields and variables related to default risk, it is necessary to account for bond recovery dynamics.

Historically estimated default loss proxies for expected default loss. It is estimated as the product of the (12-month trailing) default rate and 1 minus the senior unsecured bond recovery rate (i.e., LGD). In case of speculative-grade bond indices we always use the speculative-grade default rate instead of the overall default rate. We take the yield on the Merrill Lynch Treasury Index as our Treasury yield proxy.

Though not reported, as a first step we formally checked for stationary series using the (augmented) Dickey-Fuller (A)DF testing procedure, see Dickey and Fuller (1979) and MacKinnon (1991). Choosing lag lengths within the test regressions to prevent auto-correlated residuals, we find that the series are nonstationary whilst their first differences are stationary.

To determine whether there exist cointegration relations we use the testing methodologies of Johansen (1988, 1991) and Engle and Granger (1987). The first part of Table 5.2 reveals that, in case of speculative-grade bond indices, both the trace and maximum eigenvalue test of Johansen do not reject the null hypothesis of a single cointegration relation at the one percent level. Results are somewhat less convincing when investment-grade bond indices are considered.

The lower part of the table provides parameter estimates of the cointegration relations. It should be noted that mean and standard deviation of estimated default losses are more than twice as large when speculative-grade default rates are used instead of overall default rates. It is clear then that changes in default losses become more important when ratings decrease.

From the last column, we observe that a 1 percent rise in default loss causes a 76 basis points rise in the Master II index yield. A coefficient of one implies that changes in default loss are fully incorporated in bond yields in the long-run. The coefficients on the default loss variable are further away from one in case of rated subindices. However, we have used speculative-grade default rates instead of default rates at individual rating levels. When rating specific default rates are lower (higher) than speculative-grade default rates the corresponding coefficients on the default loss variables will be understated (overstated).

Estimating trailing default rates at more disaggregated levels becomes increasingly more difficult. Nonetheless, given a reasonable number of issuers and defaults, we estimated 12-month trailing default rates for B rated issuers separately, using Moody's DRS database. The latter series is uniformly lower than the 12-month trailing speculative-grade default rate during our sample period. Relating B index yields to Treasury rates

Table 5.2: Cointegration: Tests and Equations

Notes: This table presents cointegration tests, as well as corresponding estimated cointegration relations. The sample period runs from February 1991 to April 2007. The trace and maximum eigenvalue tests are as reported in Johansen (1988, 1991), where λ_j denotes the j'th canonical correlation. Critical values at the 5 and 1 percent level are obtained from Osterwald-Lenum (1992). The lag length of the underlying vector autoreregression (VAR) is chosen based on the likelihood ratio statistic as well as the Schwartz and Akaike information criteria. These statistics suggest that a VAR of order three would be appropriate. The lower part of the table reports estimated cointegration equations, which relate yields of rated subindices of the Merrill Lynch U.S. Corporate Master Index and the U.S. High Yield Master II Index to the Merrill Lynch U.S. Treasury Index (Treasury (All)), and Default*LGD. LGD is defined as 1 minus the U.S. 12-month trailing bond recovery rate. Default equals the U.S. 12-month trailing issuer-weighted default rate. In case of speculative-grade (investment-grade) corporate bond indices we take the speculative-grade (overall) default rate. The final row of the table provides Dickey-Fuller t-statistics, to test for stationarity of the residuals related to the cointegration regressions. Critical values are obtained from Phillips and Ouliaris (1990). Standard errors are in parentheses. a,b,c denote statistical significance at the 1, 5 and 10 percent level, respectively.

		AAA-AA			A-BBB			BB			B			CCC-C			HY Master II		
Trace Test																			
Critical Values																			
5 Percent	1 Percent	λ_j	Trace		λ_j	Trace		λ_j	Trace		λ_j	Trace		λ_j	Trace		λ_j	Trace	
34.91	41.07	0.10	34.99	b	0.12	40.18	b	0.15	49.55	a	0.17	55.56	a	0.14	49.53	a	0.16	51.88	a
19.96	24.60	0.07	14.98		0.07	15.56		0.06	16.79		0.07	19.38		0.07	20.47		0.06	18.99	
9.24	12.97	0.01	1.60		0.01	2.49		0.02	4.68		0.03	5.54		0.03	5.83		0.03	6.02	
Max Eigenvalue Test																			
Critical Values			Max			Max			Max			Max			Max			Max	
5 Percent	1 Percent		Eigenvalue			Eigenvalue			Eigenvalue			Eigenvalue			Eigenvalue			Eigenvalue	
22.00	26.81		20.01			24.62	b		32.76	a		36.18	a		29.05	a		12.97	a
15.67	20.20		13.38			13.07			12.11			13.84			14.64			6.02	
9.24	12.97																		
Cointegration Relations																			
		Coeff.	Std.Error		Coeff.	Std.Error		Coeff.	Std.Error		Coeff.	Std.Error		Coeff.	Std.Error		Coeff.	Std.Error	
c		-0.010	(0.107)		1.073	(0.102)	a	3.106	(0.222)	a	3.681	(0.310)	a	6.334	(0.708)	a	3.981	(0.260)	a
Treasury(All)		1.137	(0.018)	a	0.980	(0.017)	a	0.815	(0.037)	a	0.935	(0.052)	a	0.916	(0.119)	a	0.815	(0.044)	a
Default*LGD		0.110	(0.022)	a	0.351	(0.021)	a	0.393	(0.046)	a	0.661	(0.064)	a	1.827	(0.145)	a	0.762	(0.025)	a
Residual Stationarity																			
Lagged Differences			0			0			3			3			1			3	
Dickey-Fuller t-statistic			-3.26	b		-4.20	a		-4.66	a		-5.10	a		-4.62	a		-5.50	a

and B default losses reveals that coefficients change to 0.68 and 1.07, respectively. This confirms that default loss coefficients get closer to one once rating specific default losses are incorporated.

The estimated constant terms of the cointegration relations reveal that the average excess return of corporate bonds over Treasuries becomes larger once ratings decline. This is consistent with Altman and Bencivenga (1995), Amato and Remolona (2003) and Hull et al. (2005).

In line with Engle and Granger (1987), the last line of the table reports ADF unit-root test statistics related to residuals of the cointegration relations. Comparing these statistics to critical values from Phillips and Ouliaris (1990) reveals that the null hypothesis of no cointegration is clearly rejected.

We note that we obtain similar patterns when we replace $(P \times LGD)$ by P, see Barnhill et al. (2000). However, including both variables in one specification we get a small impact parameter of 0.06 related to P in case of the Master II cointegration relation. The default loss parameter would hardly change to 0.68. When speculative-grade rating categories are considered separately, the parameter related to P would predominantly be negative and relatively small as compared to parameters related to the default loss variable. In sum, both from a theoretical and empirical point of view, expected loss specifications are to be preferred over specifications that only incorporate default rates.

Short-Run Dynamics

We next consider short-run dynamics, using error-correction specifications. Within these specifications current corporate yield changes are related to current Treasury yield changes, default loss changes, and the variables described in Section 5.2. Residuals of the cointegration relations are included as well. The magnitude and significance of coefficients of the long-run residuals give an additional indication of the importance of the cointegration relations.

Explaining credit spread changes of individual investment- and speculative-grade bonds using a reasonable set of explanatory variables, Collin-Dufresne, Goldstein, and Spencer Martin (2001) indicate that regression residuals remain highly cross-correlated. As a result we estimate the parameters using an (unbalanced) Seemingly Unrelated Regression (SUR) framework, allowing for heteroskedastic and contemporaneously correlated residuals. Estimation results are reported in Table 5.3.

The highly significant coefficients on the residuals obtained from the cointegration relations show that, depending on the rating grade considered, each month there is a tendency to correct 5 to over 15 percent of any deviation from the long-run value. Wald tests reveal that differences between speculative-grade error-correction coefficients are statistically insignificant.

Considering the other variables, estimated coefficients once again reveal that investment-grade bond yields are predominantly driven by the yield on the Merrill Lynch Treasury Index. The positive association with Treasury yield changes decreases in magnitude, and eventually becomes negative when lower rating grades are considered. This confirms that the risk free component of the bond value decomposition becomes relatively less important once bonds become more risky. The coefficients on the one period lagged Treasury index turn out to be small and insignificant.

The short-run impact of changes in default loss increases in magnitude once ratings

Table 5.3: Error Correction Models: Investment- and Speculative-grade Bonds

Notes: This table presents error-correction models related to rated subindices of the Merrill Lynch U.S. Corporate Master Index and the U.S. High Yield Master II Index. The sample period runs from February 1991 to April 2007. The regressands (y) are corporate bond yields at the index level. The (lagged) explanatory variables, or their first differences, are: the residual of the corresponding cointegration equations of Table 5.2 (e_t); the Merrill Lynch U.S. Treasury Index (Treasury (All)); (Default*LGD), where Default equals the U.S. 12-month trailing issuer-weighted default rate, and LGD is defined as 1 minus the U.S. 12-month trailing bond recovery rate; the 3-month treasury bill rate (TBill); the Chicago Fed National Activity Index (CFNAI); the Conference Board's lagging (Δlag(%)) and leading (Δlead(%)) economic indices; the return on the Standard & Poor's 500 composite index (ΔS&P500); the volatility index of the Chicago Board Options Exchange (VIX); liquid assets held by mutual funds (MFLiquid); net new cash flows of mutual funds (MFCashFlow), where both mutual fund variables are scaled by mutual funds' aggregate net asset value; the number of positive minus the number of negative rating changes within a specific month, scaled by the number of rated issuers (Drift); the fraction of issuers receiving a speculative-grade rating (SpecGrade); the fraction of issuers receiving the lowest rating grade within the rating class considered (Minor); four seasonal 0-1 indicators (December,January, June, July); several event dummies, not reported, related to: the (aftermath of) the first gulf war (March/April 1991); the terrorist attacks on the World Trade Center buildings (October/November 2001); the subsequent loss of confidence due to 7 of the 10 largest defaults in U.S. history and/or corporate scandals (May to July 2002). Standard errors are in parentheses. a,b,c denote statistical significance at the 1, 5 and 10 percent level, respectively.

	AAA-AA			A-BBB			BB			B			CCC-C		
e_t	-0.114	(0.019)	a	-0.155	(0.022)	a	-0.091	(0.021)	a	-0.075	(0.024)	a	-0.050	(0.030)	b
ΔTreasury (All)	0.824	(0.035)	a	0.765	(0.042)	a	0.316	(0.058)	a	-0.023	(0.090)		-0.443	(0.274)	b
ΔTreasury (All)(-1)	0.084	(0.051)		0.066	(0.054)		0.102	(0.059)	c	0.059	(0.085)		-0.075	(0.252)	
Δ(Default*LGD)	-0.227	(0.074)	a	-0.238	(0.089)	a	-0.046	(0.051)		0.105	(0.079)	c	0.390	(0.255)	c
Δy(-1)	-0.049	(0.048)		-0.065	(0.045)	c	-0.070	(0.046)	c	-0.096	(0.045)	b	-0.042	(0.056)	
ΔTBill	-0.078	(0.048)		-0.002	(0.058)		0.153	(0.083)	b	0.180	(0.127)		0.603	(0.388)	b
CFNAI	0.009	(0.013)		0.007	(0.016)		-0.013	(0.022)		0.065	(0.035)	b	0.037	(0.106)	
Δlag(%)	0.041	(0.021)	b	0.056	(0.025)	b	0.059	(0.035)	b	0.217	(0.055)	a	0.648	(0.169)	a
Δlead(%)	0.001	(0.018)		0.000	(0.022)		-0.032	(0.031)		-0.036	(0.048)		0.080	(0.149)	
ΔS&P500	-0.004	(0.003)	b	-0.008	(0.003)	a	-0.004	(0.004)		-0.011	(0.007)	c	-0.030	(0.021)	c
ΔS&P500(-1)	0.000	(0.003)		-0.002	(0.003)		-0.002	(0.005)		-0.012	(0.007)	c	-0.035	(0.022)	b
ΔVIX	-0.000	(0.003)		0.000	(0.004)		0.008	(0.005)	c	0.012	(0.008)	c	0.009	(0.025)	
ΔVIX(-1)	0.003	(0.003)		0.006	(0.004)	b	0.018	(0.005)	a	0.019	(0.008)	a	0.049	(0.024)	b
ΔMFLiquid	0.006	(0.005)	c	0.005	(0.005)		-0.023	(0.016)	c	0.009	(0.025)		0.016	(0.079)	
MFCashFlow	0.004	(0.004)	c	0.000	(0.004)		-0.056	(0.008)	a	-0.095	(0.012)	a	-0.201	(0.040)	a
Drift	0.002	(0.008)		-0.005	(0.010)		-0.022	(0.015)	c	-0.008	(0.022)		-0.104	(0.068)	
ΔSpecGrade	0.020	(0.029)		0.024	(0.034)		0.042	(0.049)		0.174	(0.077)	b	0.098	(0.230)	
ΔMinor	0.002	(0.004)		0.005	(0.008)		-0.019	(0.011)	b	-0.004	(0.019)		-0.003	(0.038)	
December	-0.007	(0.025)		-0.004	(0.031)		0.053	(0.043)		-0.008	(0.067)		0.031	(0.205)	
January	-0.017	(0.026)		-0.040	(0.031)	c	-0.124	(0.043)	a	-0.150	(0.066)	b	-0.837	(0.202)	a
June	-0.035	(0.026)	c	-0.040	(0.031)		0.010	(0.044)		-0.002	(0.068)		-0.000	(0.207)	
July	0.027	(0.026)		0.018	(0.032)		0.009	(0.043)		-0.022	(0.067)		-0.269	(0.206)	c
n	193			193			194			194			194		
R-squared	0.772			0.772			0.727			0.714			0.580		
Adjusted R-squared	0.733			0.735			0.680			0.666			0.509		

decrease. The negative coefficients associated with higher rating grades can possibly be explained by a flight to quality argument. Once expected loss rises, investors gradually prefer bonds that are less vulnerable to default. This may even be BB rated bonds, when portfolio shifts within the speculative-grade bond category are considered.

The negative coefficients on lagged yield changes of the indices considered suggests that there is a tendency for overshooting, though the magnitude of the coefficients turn out to be small.

The coefficient on the change in the short or 3-month Treasury bill rate gradually becomes positive and significant once lower rating categories are considered. This is consistent with the contingent claims setting, see Merton (1974). When ratings decrease the written put becomes increasingly more important.

The coefficients on the index of lagging economic indicators are significant and increase in magnitude once ratings decrease. The estimates suggest that low grade bonds react vigorously to changes in economic conditions, which is partially corrected afterwards. On the other hand, the coefficients related to changes in CFNAI are small and insignificant. Similarly, considering the fact that the standard deviation of changes in lagging and leading economic indicators are about equal at 0.35, the coefficients on the index of leading economic indicators are quite small.

The modest impact of the index of leading economic indicators may be due to the concomitant inclusion of the stock market return. The latter can be considered as a forward looking measure.[12] Besides the current S&P500 stock market return, we also

[12] It is actually one of the ten leading economic indicators used to construct the overall Conference Board Leading Economic Index^{TM}.

include the lagged stock market return. Kwan (1996) indicates that lagged stock returns are related to current bond yield changes, but not the other way round. The current and lagged stock market return become increasingly more important once ratings decline. This is theoretically consistent. The correlation between equity and debt value should increase once default risk increases (i.e., highly leveraged firms). Similar results were obtained when indices of smaller firms were included, like the S&P400 midcap index or the S&P600 smallcap index.

The volatility index, VIX, proxies for market expectations of near term volatility (i.e., thirty day). We include both current and lagged changes in the index value. The latter proxies for volatility movements in the current month. Estimated coefficients, especially on lagged VIX, reveal that changes in the volatility index become increasingly more important once ratings decrease.

The Investment Company Institute (ICI) provides data related to different broad investment categories (e.g., corporate bonds, equity). It differentiates within broad categories as well. As a result we take both liquid assets and net new cash flows from ICI's All Bond and Income Funds subcategory when we look at investment-grade bond indices. When we consider speculative-grade bond indices the two variables relate to ICI's High-Yield subcategory.

Looking at estimated coefficients, it is clear that liquid assets held by mutual funds have no relation to corporate bond yields. On the other hand, net new cash flows have a highly significant impact on speculative-grade yields. As expected, an increase in fund flow decreases speculative-grade bond yields. Net new cash flows are not significantly related to investment-grade bond yields. Contrary to high-yield bonds, there is no separate investment-grade cash flow series. These results imply that either our investment-grade proxy is inferior, or that liquidity issues are, not surprisingly, more important in speculative-grade bond markets. The significance of the cash flow variable seems to be in line with Collin-Dufresne et al. (2001). They indicate that credit spread changes might predominantly be driven by common factor(s), most likely local supply and demand shocks.

Like Barnhill et al. (2000), we find no significant impact of minor rating classifications.[13] The coefficient on the rating drift variable and the percentage of issuers rated speculative-grade are correct most of the time, but they are hardly significant. These variables may be too general to capture current credit market conditions.

The significance and magnitude of the coefficients related to the January effect dummies allow us to differentiate between the alternative explanations described before: tax-loss selling, coupon effect, and window dressing. Contrary to the investment-grade categories, and unlike Barnhill et al. (2000), we do find a clear and highly significant January effect within the speculative-grade bond categories. The yield decrease ranges from about 13 to 86 basis points. We do not find a similar effect with respect to our June and July dummies. This indicates that the effect should be ascribed to market participants trying to prevent high-yield debt from appearing within official documentation (i.e., window dressing). The insignificant and small effects on the December dummies in turn suggest that market participants do not wait till the end of the year, but decrease their speculative-grade bond holdings more gradually.

[13] Instead of the lowest rating category within a single rating class, we include the fraction of issuers rated Aa and Baa in case of the Aaa-Aa and A-Baa series.

Not reported, looking at exceptional event dummies we observe that the end of the first gulf war caused a sharp decrease in speculative-grade bond yields. By contrast, the September 2001 attacks were followed by sharp rises in yields within the speculative-grade subcategories, with an opposite tendency afterwards. Finally, we indeed capture sharp movements in yields in the midst of 2002, though different market segments reacted differently to these events (i.e., timing).

The adjusted R^2 related to the speculative-grade yield equations ranges from 68 to 51 percent. This seems reasonable given the noisy nature of the yield series. Ljung and Box (1979) statistics reveal that there are no serious autocorrelation issues with respect to plain residuals. However, we obtain significant autocorrelations in squared residuals. As a result we considered a (diagonal) BEKK(1,1) specification as well, see Engle and Kroner (1995). Autocorrelations in squared standardized residuals are virtually absent within this alternative model specification. As expected, estimated coefficients remain largely unaffected.[14]

We finally note that if we had considered P instead of $(P \times LGD)$ within our model specifications, the impact of current changes in P on current yield changes would have been small and insignificant in case of speculative-grade bond yields. By contrast, as revealed in Table 5.3, the short-run impact of $(P \times LGD)$ becomes increasingly more important once ratings decline. This once more reveals that expected loss specifications are to be preferred over specifications that only incorporate default rates. However, incorporating P would only lead to a slight decrease in explanatory power, such that using default rates instead of default loss could be a reasonably alternative model specification.

[14] Results are available from the author upon request.

5.3.2 Maturity Split Up

Though we obtain clear differences across rating categories, the previous indices represent a blend of maturities. Merton (1974) already shows that credit yield spreads as a function of maturity of low, medium and highly leveraged firms are upward sloping, hump-shaped and downward sloping, respectively. Intuitively, highly leveraged bonds in general have low potential to worsen. On the other hand, the potential for significant improvements ceteris paribus increases in bond maturity.[15] Similarly, the impact of parameter changes within the contingent claims setting will not be uniform across different maturity ranges. For example, the average leverage ratios of issuers rated B to CCC-C increase from about 60 to 80 percent.[16] Given these leverage ratios, the marginal impact of volatility changes decreases in bond maturity.

Besides formal theoretical models there are plausible reasons why yields of bonds not only depend on maturity, but also react differently when underlying fundamentals change. Johnston (1968) already suggests that it takes time before negative shocks lead to financial difficulties. Yield spreads on bonds maturing in the near future might therefore react less severely to deteriorating economic circumstances than long-term bonds. On the other hand, refinancing debt maturing on short notice may be significantly more difficult

[15] Sarig and Warga (1989) and Fons (1994) empirically show that yield spreads decline with maturity for high yield bonds. Plotting yield series of different maturity ranges, we confirm this finding once ratings get lower. Helwege and Turner (1999) indicate that these empirical findings may be a result of selection bias when, among firms with the same credit rating, relatively safe firms tend to issue bonds with a longer maturity.

[16] These figures were obtained by matching company specific data from S&P CREDITPRO 7.0 (June 2005) with issuer rating data at year endings from 1989 to 2005. This leaves us with 1094 companies and 13772 firm-year observations. Leverage is defined as book value(bv) of debt divided by total market value(mv), or rather: total liabilities/(bv(assets)-bv(equity)-deferred taxed+mv(equity))

given unfavorable economic circumstances (i.e., crisis at maturity), especially as far as speculative-grade issuers are concerned.

In short, not distinguishing between different maturities may have a detrimental impact on parameter estimates. As a result, we split all rating categories up across four maturity ranges: 1 to 5 years, 5 to 7 years, 7 to 10 years and 10 years and beyond. Given significance of parameter estimates and data availability, we restrict ourselves to the speculative-grade bond categories. The subindices considered still represent a reasonably large underlying value. The 1 to 5 years and the 10 years and beyond maturity ranges of the CCC-C series are only available from respectively January 1997 and December 1995 onwards. Merrill Lynch offers different maturity ranges with respect to its Treasury Index as well. In the remainder we always take the subindex of the Treasury Index corresponding to the maturity range considered.

Long-Run Dynamics

Table 5.4 presents estimated cointegration relations related to different maturity ranges. Holding specific maturity brackets fixed, differences across rating categories are in line with Table 5.2. The impact of default loss changes becomes larger once ratings decline. As noted before, this can at least partially be ascribed to differences between rating specific default rates and speculative-grade default rates.

To illustrate, the last rows of Table 5.4 present results when speculative-grade default rates are replaced by 12-month trailing default rates of B rated issuers to calculate default losses. Given that the latter series is uniformly lower than the former, it comes as no surprise that default loss coefficients increase and become closer to one within maturity

Table 5.4: Cointegration: Maturity Ranges of Speculative-Grade Rated Bonds

Notes: This table presents cointegration equations considering subindices (i.e., in terms of rating and maturity) of the Merrill Lynch U.S. High Yield Master II Index. The sample period runs from February 1991 to April 2007. In contrast to Table 5.2 yields on the subindices are related to yields of corresponding maturity ranges of the Merrill Lynch U.S. Treasury Indices (Treasury), and Default*LGD. LGD is defined as 1 minus the U.S. 12-month trailing bond recovery rate. Default equals the U.S. 12- month trailing issuer-weighted speculative-grade default rate. The final rows of the table provide parameter estimates when Default is replaced by Default(B), the 12-month trailing default rate of B rated issuers. The 1-5 years and the 10 years and beyond maturity ranges of the CCC-C series are only available from respectively January 1997 and December 1995 onwards. Standard errors are in parentheses. a,b,c denote statistical significance at the 1, 5 and 10 percent level, respectively.

Maturity Range	1-5			5-7			7-10			≥ 10		
	Coeff.	Std.Error		Coeff.	Std.Error		Coeff.	Std.Error		Coeff.	Std.Error	
BB Cointegration												
c	2.684	(0.239)	a	1.432	(0.318)	a	2.467	(0.219)	a	4.465	(0.205)	a
Treasury	0.822	(0.041)	a	1.055	(0.052)	a	0.923	(0.036)	a	0.586	(0.032)	a
Default*LGD	0.567	(0.029)	a	0.471	(0.026)	a	0.278	(0.018)	a	0.292	(0.017)	a
B Cointegration												
c	4.105	(0.409)	a	3.248	(0.429)	a	2.573	(0.349)	a	3.358	(0.358)	a
Treasury	0.818	(0.071)	a	1.047	(0.071)	a	1.101	(0.058)	a	0.882	(0.056)	a
Default*LGD	1.112	(0.049)	a	0.557	(0.035)	a	0.496	(0.028)	a	0.478	(0.029)	a
CCC-C Cointegration												
c	6.931	(1.161)	a	6.026	(1.063)	a	5.481	(1.390)	a	2.855	(1.833)	c
Treasury	1.043	(0.212)	a	0.872	(0.175)	a	0.703	(0.230)	a	1.613	(0.312)	a
Default*LGD	2.348	(0.139)	a	1.806	(0.087)	a	2.186	(0.112)	a	0.282	(0.118)	a
B Cointegration Using B Default Rates												
c	6.639	(0.410)	a	4.989	(0.440)	a	4.142	(0.381)	a	4.867	(0.371)	a
Treasury	0.465	(0.077)	a	0.812	(0.076)	a	0.889	(0.066)	a	0.683	(0.061)	a
Default(B)*LGD	1.777	(0.093)	a	0.89	(0.066)	a	0.823	(0.056)	a	0.829	(0.055)	a

ranges beyond 5 years. On the other hand, it seems too simplistic to relate differences in estimated coefficients completely to differences in average default rates. In particular, the average speculative-grade default rate is more than 2 times larger than the average B default rate. When the latter series is considered instead of the former, changes in default loss coefficients are not of similar magnitude. The estimated constant terms and Treasury coefficients become larger and smaller, respectively. On the other hand, comparing residual series within specific maturity ranges, when either speculative-grade or B rated default rates are used, shows that they are closely related.

Results on the 10 years and beyond maturity range of the CCC-C series are out of line with the general pattern. This might be a result of the shorter underlying estimation period. Estimating coefficients recursively gives a slight indication of parameter instability in the latter case, especially as compared to the other relations considered.

Keeping rating categories fixed instead, it seems that the impact of changes in default loss becomes smaller once underlying maturities increase. This is consistent with Merton (1974). The potential of significant value improvements is lowest when bond maturities are short. As a result, short maturity bonds will respond more vigorously to changes in expected default loss.

More directly, we can again point at default rate calculations. Figure 5.1 plots average yearly default intensities as a function of underlying calculation periods. In case of B and CCC-C issuers average yearly default intensities decline when longer underlying calculation periods are considered.

Short-Run Dynamics

Table 5.5 reports estimated short-run specifications, using the SUR estimation methodology. We exclude variables that had no significant and consistent explanatory power in Table 5.3, like the minor rating classification dummy. The estimated coefficients on residuals of the cointegration relations of Table 5.4 remain highly significant. The adjustment speed depends on the market segment considered, ranging from 6 to over 20 percent per month. Dissimilarities across maturity ranges and rating categories are confirmed by Wald tests.[17]

In line with Table 5.3 the short-term impact of changes in default loss is almost consistently negative and small in case of the BB maturity ranges. This may again be explained by a flight to quality argument. The impact coefficients become positive and increasingly more important when ratings decline, especially so at shorter maturity ranges. As noted, the latter might at least partially be ascribed to differences in default rate calculations.

Given specific rating categories, the patterns observed across maturity ranges with respect to the 3-month Treasury bill rate and VIX can be directly related to Merton (1974). As stated in Section 5.3.2, the average leverage ratios of issuers rated B to CCC-C increase from about 60 to 80 percent. From a theoretical point of view, changing the short rate across different underlying bond maturities gives a downward sloping impact curve when the leverage ratio is 60 percent. When leverage increases to 80 percent the curve slopes downward for short maturities, but gradually slopes upward for medium

[17]Estimation results are similar when we replace speculative-grade default rates by B rated default series to calculate default losses of B rated issuers.

Figure 5.1: Average Yearly Default Intensities of Ba, B and Caa-C Rated Issuers

Notes: This figure depicts average yearly default intensities of Ba, B and Caa-C rated issuers related to different (calculation) periods. Average yearly default intensities are calculated along the lines of Hull et al. (2005). That is, $\bar{\lambda}(t) = -\ln(1 - Q(t))/t$, where $Q(t)$ denotes the average cumulative issuer-weighted corporate default rate of the whole letter rating considered over a t year period. The latter are reported by Moody's Investors Service, see Cantor et al. (2006).

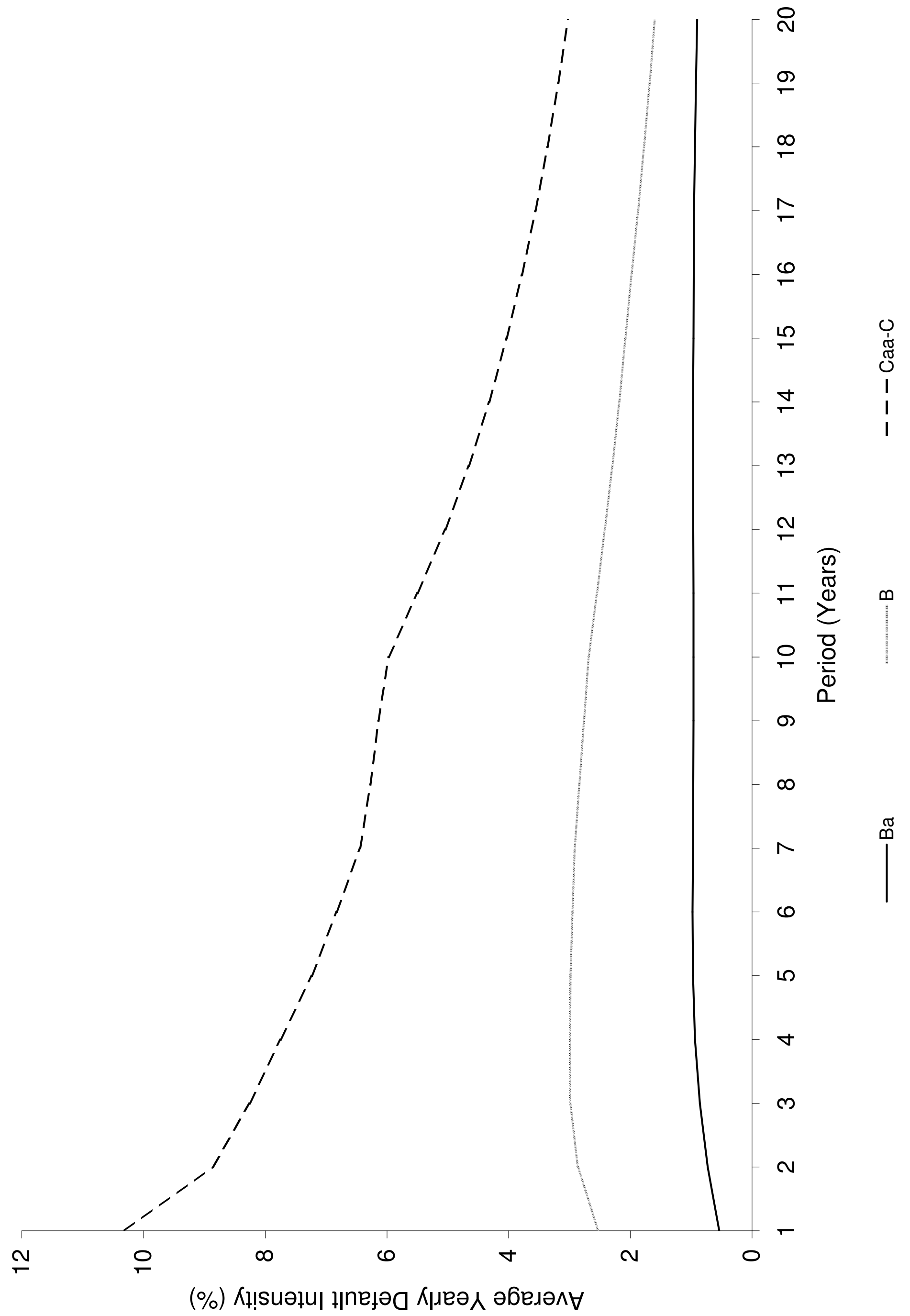

Table 5.5: Error Correction Models: Speculative Grade Maturity Ranges

Notes: This table presents error correction models considering subindices (i.e., in terms of rating and maturity) of the Merrill Lynch U.S. High Yield Master II Index. The sample period runs from February 1991 to April 2007. The residuals (e_t) correspond to related cointegration equations of Table 5.4. LGD is defined as 1 minus the U.S. 12-month trailing bond recovery rate. Default equals the U.S. 12-month trailing issuer-weighted speculative-grade default rate. Like Table 5.4, we always include the corresponding maturity range of the Merrill Lynch U.S. Treasury Indices (Treasury). The other variables are as described in Table 5.3. The 1-5 years and the 10 years and beyond maturity ranges of the CCC-C series are only available from respectively January 1997 and December 1995 onwards. Standard errors are in parentheses. a,b,c denote statistical significance at the 1, 5 and 10 percent level, respectively.

	BB				B				CCC-C			
	1-5	5-7	7-10	$\geq$ 10	1-5	5-7	7-10	$\geq$ 10	1-5	5-7	7-10	$\geq$ 10
e_t	-0.093 a	-0.185 a	-0.104 a	-0.146 a	-0.151 a	-0.067 a	-0.131 a	-0.271 a	-0.139 a	-0.097 a	-0.058 a	-0.197 a
ΔTreasury	0.318 a	0.262 a	0.352 a	0.364 a	-0.177 c	0.022	0.143 b	0.213 b	0.001	0.058	-0.665 a	0.065
ΔTreasury(-1)	-0.155 a	0.135 a	-0.049	-0.023	-0.018	-0.012	-0.062 c	-0.234 a	0.222 a	0.058	-0.068	0.121 b
Δ(Default*LGD)	-0.071	0.005	-0.047	-0.074	0.239 b	0.068	0.095	-0.011	0.399	0.548 b	0.850 a	-0.182
Δy(-1)	0.135 c	-0.040	0.137 a	0.070	-0.023	0.013	0.006	0.102	-0.247	0.291	0.041	-0.238
ΔTBill	0.189	0.259 a	0.111 b	0.047	0.320 c	0.095	0.054	-0.197	1.184 c	-0.297	-0.018	0.434
CFNAI	-0.051 c	0.017	0.008	0.022	0.170 a	0.043	0.065 b	-0.027	0.024	-0.078	0.125	-0.496 a
Δlag(%)	0.079 c	0.045	0.045 c	0.109 a	0.362 a	0.165 a	0.206 a	0.170 b	0.902 a	0.470 b	0.582 a	1.030 a
Δlead(%)	-0.023	-0.058 c	-0.034 c	-0.051 c	-0.144 b	-0.026	-0.060	0.009	0.540 b	-0.237	-0.251 c	0.119
ΔS&P500	0.004	-0.005	-0.007 b	-0.007 c	-0.007	-0.011 c	-0.009 c	-0.004	-0.029	-0.019	-0.027	-0.014
ΔS&P500(-1)	0.004	0.004	0.001	-0.006	-0.008	-0.007	-0.007	0.002	-0.051	0.009	0.002	-0.014
ΔVIX	0.015 c	0.007	0.001	-0.002	0.023 c	0.021 a	0.009	-0.006	0.018	-0.020	0.035	0.026
ΔVIX(-1)	0.025 a	0.024 a	0.013 a	0.010 b	0.031 b	0.029 a	0.013 b	0.013	0.051	0.080 a	0.042 c	-0.001
ΔMFLiquid	0.006	-0.015	-0.012	-0.018	0.081 b	0.034	0.023	0.015	0.099	0.042	0.056	0.061
MFCashFlow	-0.095 a	-0.053 a	-0.055 a	-0.040 a	-0.102 a	-0.100 a	-0.101 a	-0.092 a	-0.334 a	-0.159 a	-0.192 a	-0.187 b
Drift	-0.039 c	-0.044 a	-0.021 b	-0.025 c	-0.014	-0.026	-0.026	0.059 b	-0.135	-0.200 b	-0.007	-0.138
ΔSpecGrade	0.139 c	0.055	0.066 c	-0.006	0.301 b	0.241 a	0.171 b	0.048	0.310	0.293	0.120	-0.142
December	0.114 c	0.052	0.047 c	0.005	0.121	0.024	-0.005	0.010	0.201	0.128	0.041	-0.328
January	-0.205 a	-0.103 b	-0.061 b	-0.151 a	-0.265 b	-0.091	-0.103 c	-0.200 b	-0.945 b	-0.576 b	-0.519 b	-1.247 a
June	0.012	-0.022	0.018	0.000	-0.045	0.051	0.031	-0.145 c	-0.470	-0.042	0.396 c	0.099
July	0.077	0.002	-0.010	-0.045	-0.179 c	0.012	0.000	-0.130 c	-0.381	-0.405 c	0.040	-0.081
n	194	194	194	194	194	194	194	194	122	194	194	135
R-squared	0.611	0.767	0.756	0.559	0.745	0.601	0.617	0.779	0.47	0.455	0.623	0.367
Adj. R-squared	0.548	0.729	0.717	0.488	0.703	0.536	0.554	0.743	0.333	0.366	0.561	0.222

and long maturities. Estimated coefficients on the Treasury bill rate grossly reveal such patterns. However, their magnitudes should in general be closer to one, and are certainly not allowed to become negative.

Considering the volatility index instead confirms our earlier finding. Only lagged VIX values, representing current volatility changes, significantly affect current yield changes. From a theoretical point of view, given speculative-grade leverage ratios, the marginal impact of volatility changes decreases in bond maturity. The curve becomes steeper when leverage increases. This is almost exactly what is revealed empirically. The impact of volatility changes becomes smaller when underlying maturities rise within the BB and B categories. This is confirmed by Wald tests. Results in the CCC-C category are less consistent.

Estimated coefficients on changes in the index of lagging economic indicators consistently point in a positive direction, which is in line with overshooting. Results within rating classes are more or less uniform. Within each maturity range the impact is larger once ratings deccrease. These tendencies are confirmed by Wald tests. The index of leading economic indicators in general has a negative impact on bond yields, though effects are small and insignificant. Similarly, we do not find a significant and consistent impact on the contemporaneous U.S. economic activity index, CFNAI.

The coefficients on contemporaneous changes in the stock market index indeed reveal a clear and increasingly negative pattern across rating categories. However, as compared to Table 5.3, considering different maturity ranges clearly compromises on significance.

The estimated coefficients on the monthly dummy variables confirm the existence of a January effect, that might best be ascribed to window dressing. The January effect is significant and quite uniform within all rating categories. Like Table 5.3, the effect is largest within the lowest rating category, and turns out to be similar within rating categories.

The remaining explanatory variables generally have a uniform impact within specific rating categories. This is confirmed by Wald tests. Differences show up predominantly across rating categories.

5.4 Conclusion

This chapter studies short- and long-run dynamics of speculative-grade bond yields. We obtain cointegration relations between speculative-grade bond yields, Treasury yields and estimated default losses. In line with prior research, the cointegration relations reveal that average excess returns of corporate bonds over Treasuries increase when ratings decrease.

Even when investors require a spread over the risk-free rate in excess of expected default losses, we might still expect that a unit change in expected default loss would be fully reflected in corporate bond yields in the long-run. The estimated default loss coefficient is close to one when it is possible to use rating specific default rates to estimate default losses in case of B rated issuers. Estimated coefficients on the default loss variable will be understated (overstated) when we are forced to use speculative-grade default rates that overestimate (underestimate) the corresponding rating specific default rates.

Like long-run dynamics, short-run dynamics of investment-grade yields are determined by Treasury yields. Besides changes in expected default loss and bond liquidity, short-run dynamics of speculative-grade yields are determined by factors associated with structural models, such as changes in the short rate and stock volatility. We also find a clear January effect with respect to speculative-grade bond yields. This can most likely be ascribed to window dressing.

Splitting bond indices up across different maturity ranges, and holding maturities fixed, we obtain similar long-run dynamics within rating categories. Nonetheless, in general short maturity bonds respond more vigorously to changes in expected default losses.

Looking at error-correction specifications, short-run adjustment to long-run errors depends on the maturity range considered. Consistent with Merton (1974), we also obtain dissimilarities across maturity ranges with respect to changes in the short rate and stock market volatility. Other explanatory variables in general have a uniform impact within specific rating categories. Differences show up predominantly across rating categories.

Finally, though explanatory power is comparable, expected loss specifications are to be preferred over specifications that only incorporate default rates, both from a theoretical and empirical point of view. Estimated coefficients on the default loss variable are more significant and robust across alternative model specifications.